Fuel price and income elasticities of the road transport demand in Europe: a dynamic panel data analysis

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Abstract

This article proposes an econometric analysis of the demand for mobility, vehicle stock and new registrations in the European road sector (EU-27 Member States + Croatia and Norway). The role played by different variables on road traffic is estimated using dynamic panel-data modeling at the European level and by clusters. Counter to GDP per capita, which appears to be an unavoidable driver of the road transport demand, we find statistically significant fuel price elasticities for only one third of the estimated models. Furthermore, the magnitude of the influence of these determinants differs widely between three distinct groups of countries. Taken together, these results encourage policymakers to design national-level measures lowering the purchase costs rather than specific action on fuel taxes in order to reduce CO_2 emissions of the European transport sector.

JEL codes: R40; C23.

Keywords: road transport demand; Europe; dynamic panel data.

1 Introduction

Transport contributes almost 25% of all Europe's greenhouses gases (GHG) emissions.[1] Cars and vans produce 15% of EU's CO_2 emissions, the main grenhouse gas.[2] Despite efforts to reduce CO_2 emissions from transport, increasing vehicle fleet and trafic volumes led to increased CO_2 emissions when the other sectors decreased their emissions. Thus, there is a growing urgency to focus in decarbonising the EU transport sector. Faced with this situation, and due to this sector's high dependency on fossil fuels, the European Commission (EC) has set itself the target of reducing the greenhouse gas (GHG) emissions of transport by 20% by 2030 by comparison with their 2008 level. In addition, within the framework of its 2050 roadmap (EC, 2011), the EC has identified a potential reduction of GHG emissions by 60% compared with 1990.

Road transport is definitely a factor for economic growth, yet in a context of scarce energy resources, this kind of expansion may engender a set of problems (greater dependence on foreign energy sources, higher GHG emissions) that need to be addressed more urgently by policymakers. Understanding road transport demand has increasingly become a core public policy issue and serves as the focus of this paper. The concerns about global warming have reignited interest in explaining cross-country differences in fuel consumption, car ownership and automobile driving. Over the past decades, numerous studies have studied the causal relationship between transport (or car) demand and several independent variables such as gross domestic product (GDP) per capita, employment, population, etc. A wide variety of models have been estimated, using different functional forms and estimations, covering different time periods in the effort to better understand road transport demand and consecutive fuel consumption.

Compared to this literature which generally focus on one country (cf. Section 2), we choose to yield a cross-country analysis of the European road transport demand by applying a dynamic panel data methodology to 29 European countries (EU-27 Member States + Croatia and Norway). From an original database, this paper attempts to determine the most important drivers of the demand for road travel in Europe over the period 1990-2012. We assume that the latter can be expressed as a function of fuel prices, GDP per capita and some other factors in order to estimate their respective short and long-term elasticities. Three different dependent variables

[1]European Commission. Reducing emissions from transport. `http://ec.europa.eu/clima/policies/transport_en` (last consulted 14 February 2017)

[2]European Commission. Road transport: Reducing CO_2 emissions from vehicles. `https://ec.europa.eu/clima/policies/transport/vehicles_en` (last consulted 14 February 2017)

have been chosen to proxy the road transport demand: i) the mobility as measured by Vehicle-Kilometers Traveled (VKT), ii) the vehicles stock and iii) new cars registrations. As expected, when statistically significant, we find positive GDP per capita elasticities and negative fuel price elasticities, regardless of the dependent variable considered. In absolute terms, GDP per capita elasticities appear to be systematically higher than fuel price ones. Apart from presenting these results in detail, this article also conducts separate analysis for three different kind of countries. This distinction leads to attempt to evaluate whether groups of countries show different behavior responses with respect to both fuel price and GDP per capita changes. Our results show that drivers, and their associated coefficients values, vary from one group to another. Finally, we find statistically significant fuel price coefficients for only one third of the estimated models whereas GDP per capita coefficients appear to be always statistically significant.

The remainder of this article is organized as follows. Section 2 reviews existing literature. Section 3 describes both data series and the panel data models used to estimate demand elasticities. Section 4 contains the empirical results and Section 5 concludes by highlighting some of these results and their policy implications.

2 Literature review

A large number of econometric studies have attempted to estimate how demands for car and road transportation relate to the price of fuel and income. Many papers included both income and fuel price elasticities. Most empirical studies provide elasticities derived from national or regional data and different econometric approaches are used to estimate the elasticities: OLS (Gillingham, 2014), instrumental variables (Gillingham, 2014), error correction model (Odeck & Johansen, 2016), pseudo-panel (Dargay & Vythoulkas, 1999), GMM-based methods (González & Marrero, 2012), etc. Although, these differences make comparison difficult, it is generally agreed that GDP per capita (or income) positively impacts mobility by car, new registration and vehicle stock while the fuel price negatively impacts them. In looking at a significant body of literature, the other main results regarding the income and price elasticites of vehicle stock, new registration and car mileage demand can be summarized as follows.

Long-run (LR) elasticities are greater than short-run (SR) elasticities (mostly by factors of 2 to 3, in absolute terms).[3] For example, estimating travel demand elasticity with respect to

[3]Nevertheless, for the Norwegian case, Odeck & Johansen (2016) found lower income elasticites compared to their fuel price counterparts. The explanation may lie in the relatively high disposable income in this country.

fuel prices in Norway, Odeck and Johansen (2016) estimated a value of -0.11 in the short-run and -0.24 in the long run. Looking at the demand for transport in Spain, González and Marrero (2012) estimated that short-term fuel price elasticity was -0.282 while the long-term elasticity was -0.607.

Income elasticities are generally greater than price elasticities (mostly by factors 1.5 to 3). For example, quantifying Canadian fuel price and income elasticities for vehicle travel for the period 1990-2009 with a cointegration model, Boilard (2010) estimated the values of price elasticites to be -0.046 (SR) and -0.085 (LR) while the values of income elasticities are 0.169 (SR) and 0.423 (LR). Income elasticities based on GDP are generally higher than those obtained from household incomes (Dunkerley et al., 2014).

The trend of elasticities may be a decrease overtime (Fouquet, 2012; Van Dender & Clever, 2013). According to Fouquet (2012), the explanation of the income elasticites decrease may lie in saturation of car ownership. At the same time, fuel price elasticities decrease results from the combined effect of decreasing prices and increasing incomes.

In addition to fuel price and GDP per capita (or income), social and demographic changes may also impact transport use. More recently, literature has concentrated on explanatory variables such as urban density (Rodrigue et al., 2006, Hankey & Marshall, 2010), employment (Jong & Ven de Riet, 2008) or age distribution (Sivak & Schoettle, 2012; Kuhnimhof et al., 2012a, 2012b).

3 Methodology

This Section first describes the dataset we have compiled. A brief description of the econometric technique used is then provided.

3.1 Data

This study uses a panel of 29 European countries (EU-27 Member States + Croatia and Norway) over the period 1990-2012. The corresponding database was compiled from several sources: *Odyssee*, *Global Energy*, World Bank, United Nations Economic Commission for Europe (UN-ECE).[4] As depicted in Table 1 we selected variables providing information on five main categories: i) Population, ii) Road Network, iii) Economics, iv) Mobility and automotive market, iv) Fuels and fuel markets. The influence of these variables on mobility demand, vehicle stock and

[4] *Odyssee* and *Global Energy* databases are povided by ENERDATA.

new registrations are estimated using panel-data econometrics. Given the great disparity between countries in Europe, we have chosen to categorize them in three slightly more homogenous groups according to their economic situation and the degree of maturity of their automobile market[5]: *Group 1*, *Group 2* and *Group 3*.

<Insert Table 1 here>

We now turn to the presentation of the econometric specifications.

3.2 Econometric specification and estimation methods

This article estimates the determinants of road transport demands by using econometric methods. Time-series representing the evolution from 1990 to 2012 of *i)* either mobility, *ii)* or stocks *iii)* or new registrations of each of the $29-th$ European countries are used to estimate over time the relationship between automobile ownership behavior and a variety of socioeconomic and policy variables. This section will present both the Econometric specification and the underlying estimator chosen to do so.

3.2.1 A dynamic panel data modelling

According to the discussion presented in previous sections, the factors driving road traffic are mainly fuel prices, including taxes, income, socioeconomic aspects and vehicle characteristics. Yet the influence of these factors also depends on road transport market maturity, which varies widely among the twenty-nine countries identified above. Following this discussion and to take into account the latter criteria (*i.e.* dissimilar road transport market maturities), the impact of these variables on road traffic will be estimated using panel-data econometrics. As detailed below, cross-sectional units of the panel-data sample correspond to these twenty-nine countries. Moreover, our panel-data sample is closer to time series data than to cross-sectional data; it thus appears suitable to include the lag dependent variable among the regressors for studying the determinants of road transport demand for European countries. This specification is in line with the models put forth by the majority of authors, such as Hansen & Huang (1997), Noland

[5]Countries were grouped via a principal component analysis and according to expert judgments. As we will see, this classification is confirmed by econometrics analysis.

(2001), Cervero & Hansen (2000), Noland & Cowart (2000), Fulton et al. (2000), Hymel et al. (2010), and Gonzalez et al. (2012).

Applying dynamic panel-data modeling techniques, the following econometric specification is proposed to test for the influence of previously identified road traffic determinants:

$$ly_{i,t} = \gamma ly_{i,t-1} + X'_{i,t}\beta + \alpha_i + \epsilon_{i,t}, \quad \forall i,\ t \tag{1}$$

with $t = \{1990, \ldots, 2012\}$ being the period over which road traffic data have been obtained, and i the 29 countries considered. $ly_{i,t}$ is the logarithm of the i-th country's road traffic demand at time t. The dynamic nature of the model requires introducing a lag for the traffic variable among regressors ($ly_{i,t-1}$). $X'_{i,t}$ is the vector of explanatory variables summarized previously (see Table 1)[6] and β is the $(K \times 1)$ vector of corresponding parameters to be estimated. There are thus K regressors in $X'_{i,t}$ $(= (x^1_{i,t}, x^2_{i,t}, \ldots, x^k_{i,t}, \ldots, x^K_{i,t})\ \forall i,\ t)$ not including a constant term and, as is typical, $(\alpha_i + \epsilon_{i,t})$ correspond to the composite error term.

3.2.2 Estimation methods

The panel-data sample used in this paper to estimate Eq. (1) is a long-panel dataset.[7] Moreover, the econometric specifications of Eq. (1) is characterized by a dynamic structure that specifies the dependent variable for an individual ($ly_{i,t}$) to be partially dependent on its value during previous periods ($ly_{i,t-1}$). Thus, it is well-known that conventional panel-data estimation approaches, such as the *Fixed Effects* or *Random Effects* estimators, are not appropriate as $ly_{i,t-1}$ is not a strictly exogenous regressor but a weakly exogenous (predetermined) variable. To solve this endogeneity problem and to control for the fixed effects represented by the α_i[8] at the same time, one have to first-differencing rather than mean-differencing Eq. (1) to remove the fixed effect. Our generic econometric specification Eq. (1) thus becomes:

$$\Delta ly_{i,t} = \gamma \Delta ly_{i,t-1} + \Delta X'_{i,t}\beta + \Delta\epsilon_{i,t} \tag{2}$$

Where $\epsilon_{i,t}$ is now assumed to be serially uncorrelated. Consistent estimator can then be obtained by Instrumental Variables (IV) estimation of the parameters in the first-difference model

[6] All variables are expressed in natural logs, unless otherwise specified.

[7] Long-panel datasets are characterized by a relatively small number of individuals and a relatively long time period (N is small and $T \to \infty$).

[8] In panel data modeling, the α_i account for those fixed and inherent factors in each European country that are not explicitly considered in the model, such as geographic and social characteristics, local policies and other initial conditions.

(Eq. (2)), using appropriate lags of regressors as the instruments for the transformed variables of the weakly exogenous (predetermined) regressors. This two-step estimation procedure – *i)* first-differencing rather than mean-differencing Eq. (1) and then *ii)* applying a kind of IV approach to Eq. (2) – has been proposed by Anderson and Hsiao (1982), Holtz-Eakin et al. (1988), and Arellano and Bond (1991), among others.

The former was the first to propose IV estimation using $\Delta ly_{i,t-2}$ or simply $ly_{i,t-2}$ – which is uncorrelated with $\Delta\epsilon_{i,t}$ as long as the errors are serially uncorrelated – as an instrument for $\Delta ly_{i,t-1}$ in Eq. (2), for all i and $t \geq 3$. The regressors $x_{i,t}$ are used as instruments for themselves as they are strictly exogeneous.

Although this *two-stage least squares* estimator is consistent, Holtz-Eakin et al. (1988) and Arellano and Bond (1991) pointed out it is not asymptotically efficient when the panel has more than three time series observations, which is the case here. These authors propose an alternative approach based on the Generalized Method of Moments (*GMM*). Compared to the Anderson-Hsiao estimator, the basic idea is to more fully utilize all information available in the dataset by employing the levels of the dependent variable lagged two periods or more (*i.e.* ly_{it-s} for $s \geq 2$) as instruments in the *GMM* procedure to overcome the problem of $E(\Delta ly_{it-1}\Delta\epsilon_{it}) \neq 0$ in the first difference model (Eq. (2)). In offering these additional instrumental variables, the *GMM* estimator proposed by Arellano and Bond (1991) leads to more efficient estimates.

This (one-step) *GMM* estimator is also called the Arellano-Bond estimator after Arellano and Bond (1991), who detailed the implementation steps for the estimator and proposed tests on the assumption that $\epsilon_{i,t}$ are serially uncorrelated: the $m1$ and $m2$ tests. These two tests are the most widely used tests for validating the assumptions involved in the *GMM*[9]. They correspond to first-order and second-order serial correlation tests of the estimated residuals, respectively. They are based on the standardized residual covariance matrix and are asymptotically $N(0,1)$ under the null hypothesis of no autocorrelation: $Cov(\epsilon_{i,t}, \epsilon_{i,t-k}) = 0$ for $k = 1,\ 2$. If the error component $\epsilon_{i,t}$ in Eq. (1) are serially uncorrelated, we would expect to reject the null hypothesis at order 1 (the $m1$ test) but not at order 2 (the $m2$ test). Thus, there should be evidence of negative first-order serial correlation and no evidence of second-order serial correlation (or higher orders) in the first differences of the errors $\epsilon_{it} - \epsilon_{it-1}$.

[9] Another test is the Sargan test, which checks the validity of the instruments used. This test is less reliable (and used) in cases like ours, since it requires that the errors be independent and identically distributed, an unreasonable assumption in our case.

4 Estimation results

The three following subsections will discuss the estimation results of Eq. (1), expressed in first-differences (see Eq. (2)). Regarding the dependent variable, $ly_{i,t}$ in both equations, we have chosen to express the road transport demand in three different ways: *i)* the (logarithm of) mobility ($Mobility_{i,t}$), *ii)* the (logarithm of) car stock ($Stock\ of\ cars_{i,t}$), and *iii)* the (logarithm of) new registrations ($New\ registrations_{i,t}$). In other words, three distinct models are presented thereafter depending on the variable chosen to proxy road transport demand in Eq. (1) and Eq. (2): $ly_{i,t} = \{Mobility_{i,t}, Stock\ of\ cars_{i,t}, New\ registrations_{i,t}\}$.

All results are estimated thanks to the Arellano and Bond (1991) panel data method; conventional panel-data estimation approaches being not appropriated and hence not presented herein, as explained in the previous Section. Unless otherwise indicated, regression results are presented in reduced form (see Table 2, Table 3, Table 4). These models were chosen with the general-to-specific approach applied to econometric modeling. As is customary, " *** ", " ** ", and " * " respectively indicate 1%, 5% and 10% significance levels; the (robust) standard errors of the coefficient estimates are reported in brackets. In each column, the dash " $-$ " means that the variable under consideration has not been included in the model: the reason for this exclusion is not that the variable coefficient estimate was not statistically significant at the 10% level, but rather because inclusion as a determinant of the variable of interest was considered irrelevant. Note that all estimation results are solely presented in their reduced form, unless otherwise specified. Regarding model information, *Number of observations* and *Number of groups* indicate, respectively, the number of observations and the corresponding cross-sectional units of the panel-data sample used to perform each regression. Not that for a large T (relative to cross-sectional units), the Arellano-Bond method generates many instruments, thus leading to a potential poor performance of asymptotic results. This argument explains why the *number of instruments* has been restricted to $ly_{i,t-2}$ and $ly_{i,t-3}$ in each estimates. In all Tables, the quality of regressions is verified by the Wald statistic and specification tests $m1$ and $m2$. In most cases, no evidence is derived from these serial correlation tests that the reduced forms of the estimation results have been misspecified[10].

[10] Recall that the value of the statistic $m1$ must be negative and its associated p-value should be smaller than α (the significance level defined), while the p-value associated with the $m2$ test should be high (greater than α, at least).

In the folllowing subsections, Section 4.1 will analyze the main mobility demand drivers (presented in Table 2), whereas Sections 4.2 and 4.3 will focus respectively on determinants of the evolution of vehicle fleets (Table 3) and new car registrations (Table 4). In each Tables, the first column presents short-term elasticitiy estimates for the whole sample whereas columns 2 to 4 show these results for the 29 European countries clustered into three more homogenous groups, namely *Group 1*, *Group 2* and *Group 3* (see Table 1).

4.1 The determinants of mobility demand

Table 2 contains the results for mobility demand determinants. Note that this Section and the following two (Sections 4.2 and 4.3) only focus the analysis on the signs and significance of the coefficients estimated as the comparison of these elasticities with estimations in the related literature, as well as the distinction between short-term and long-term elasticities, will be discussed below (see Section 5, Table 5).

<Insert Table 2 here>

We first begin with the comments on the whole sample (colmun (1)). The dynamic panel data modelling strategy is accurate since the lagged dependent variable ($Mobility_{i,t-1}$) is statistically significant at the 1% level. This lag term accounts for the short-term dynamic and for the conditional convergence among European countries in relation to the road traffic demand variable. A significant γ coefficient between 0 and 1 would be indicative of this variable's conditional convergence. The larger the coefficient, the greater the effect of the inertia as an explanatory factor of its own evolution, as well as the slower the convergence speed among the countries. The coefficient of $mobility_{i,t-1}$ is positive and rather high (0.6903), thus indicating a positive influence of the previous mobility demand in country i ($mobility_{i,t-1}$) on its growth rate. It comes as no surprise that the coefficient of *GDP per capita* is statistically significant at the 1% level and positive, which indicates that mobility demand also depends positively on economic activity (as measured in terms of *GDP per capita*). As for *fuel price*, our results indicate that they have a negative and significant incidence on road traffic mobility, which is in line with the theory. On average, *i.e.* for the whole sample, the estimated short-term fuel price elasticity is -0.1145 and its coefficient is significant at the 1% level. Regarding the effect of average per-vehicle fuel consumptions on the evolution in mobility demand; the negative sign of the *Average consumption* coefficient (-0.3912) seems to corroborate the existence of a *rebound effect* at the European level: the higher the energy gains on average per-vehicle fuel consumptions, the higher the growth rate of road transport mobility.

Last but not least, the variable *Groups* is statistically significant at the 1% level. This dummy variable takes the values 1, 2, 3 if the country under consideration belongs respectively to the group 1, 2, 3. Its positive sign indicates that, *ceteris paribus*, the growth rate of mobilty is more important in the western European countries (*Group 3*) than in the *Group 2* and *1*'s countries. The statistically significance of this coefficient validates the choice done in this paper that the whole sample results for the European transport demand can effectively be further investigated by breaking them up according to three more homogenous clusters of countries, namely *Group 1*, *Group 2* and *Group 3*.

When comparing results at the cluster level (see columns (2) to (4)), only comments on the variables $Mobility_{i,t-1}$ and *GDP per capita* appear to be applicable regardless the sub-sample under consideration. Regarding the $mobility_{i,t-1}$ variable, the coefficient estimate magnitude, which lies between 0.64 and 0.75, tends to indicate a rather robust and significant evidence of no conditional convergence among European countries regarding the evolution of the mobility demand. The coefficients of *GDP per capita* is not statistically different between the group 2 and the group 3 (0.28), which is not the case for the group 1 (0.41). Thus, the demand for mobility of group 2 and 3 reacts in the same way to the variations of the the economic activity and appears to be less sensitive to this driver than the group 1's countries. Regarding the effect of *fuel price*, this coefficient is statistically significant at the 1% level for the Group 3 (see column 4) and for the whole sample (column 1), but have no impact on the demand for mobility in the two other group of countries (columns 2 and 3). This result tends to justify our analysis by sub-samples/clusters as a simple analysis at the aggregate level (column 1) would yield to the conclusion that the European mobility is negatively impacted by the evolution of fuel prices, while the price elasticity of the European mobility is actually only statistically significant in the group 3's countries, *i.e.* the ones among the 29-*th* with the highest maturity degree of automotive market. The same conclusion can be drawn from the variable *Average consumption*. At the aggregated level, this variable seems to have a negative impact on the European mobility as its coefficient is negative and statistically significant at the 1% level (column 1) while at the sub-sample level it only appears statistically significant for the groups 2 and 3 (see columns 2 and 3).

4.2 The determinants of vehicle inventory

Table 3 lists the estimates of determinants for vehicle inventory (*Stock of cars*). As for Table 2, the first column provide the estimates for the whole sample. The three other columns present the estimates for the three sub-samples. Compared to Section 4.1, we only briefly comment notable differences specific to the determinants of the vehicle inventory evolution since the majority of explanatory variables remain the same.

<Insert Table 3 here>

In each model (columns (1) through (4)), the previous evolution of *Stock of cars* in country i ($mobility_{i,t-1}$) has a statistically significant and positive influence on the growth rate the dependent variable (*Stock of cars*), ranging from 0.67 (*Group 1*) to 0.86 (*Group 2*). The vehicle inventory appears to be positively driven by the evolution in economic activity (as measured in terms of *GDP per capita*). The range of the coefficient estimates – from 0.14 (*Group 1*) to 0.17 (the whole sample) – indicates that the elasticity of the stock of cars to the economic activity is rather stable and relatively low among European countries. Compared to the drivers of the mobility demand, the fuel price do not appear as a determinant of the evolution of the stock of cars, which is rather intuitive. Actually, the most notable difference compared to Section 4.1 rely on the sign of the variable *Groups* which become negative (see column (1)); meaning that the growth rate of the stock of cars is, *ceteris paribus*, less important in the western European countries (*Group 3*) than in the *Group 2* and *1*'s countries. This negative sign, combined with the negative one of the *Average consumption* coefficients, reinforce our claim of the existence of a *rebound effect* at the European level.

4.3 The determinants of new registrations

Table 4 provides the estimates of determinants for new car registration (*New registrations*). As usual, column (1) presents the estimates results of new car registrations (*New registrations*) for the whole sample. Columns (2), (3) and (4) list estimates for the same models yet for the sub-samples.

<Insert Table 4 here>

Regarding the new registration determinants (*New registrations*), the coefficient of *New registrations*$_{i,t-1}$ is positive, thus indicating a positive influence of the previous evolution of registered cars from country i ($Newregistrations_{i,t-1}$) on the current registration growth rate (*New registrations*). One can notice however that compared to previous estimates the magnitude of this effect is less important; indicating a conditional convergence among European countries regarding the evolution of the new registrations. Not surprisingly, a number of previous determinants identified for both mobility (*Mobility*) and vehicle inventory (*Stock of cars*) also have an impact on new registrations (*New registrations*), namely: i) the economic activity (*GDP per capita*) maintains a positive impact on new registrations (*New registrations*) regardless the sub-sample under consideration, while the *fuel price* only have a negative (and statistically significant) for Group 2's countries. Lastly, as for the evolution of stock of cars, the growth rate of new registrations appears to be more important in countries belonging to Group 1 and 2 than those belonging to Group 3; corroborating the existence of a stagnant automotive market in countries with the highest maturity degree.

5 Discussion and concluding remarks

The modeling of road transport demand has become an increasingly pivotal topic in public policy. Using a database covering 29 countries over the 1990-2012 period, we carried out an econometric analysis of the main road transport determinants within European countries; providing estimates at the European level and by clusters. Three distinct models have been estimated in this article, depending on the variable chosen to proxy the European transport demand: mobility (veh-km), vehicle fleet and new vehicle registrations. All results have been estimated thanks to the Arellano and Bond (1991) method, an efficient estimator for estimating short-term elasticities in dynamic panel data models. Recall Eq. (2), β_i would reflect the short-term elasticity between road traffic demand and the x_i variable, with the remaining factors conditioned.

Another interest of dynamic panel data models such as specified in Eq. (2) is that long-term elasticities can be easily computed from the short-term ones. In these models, long-term elasticities correspond to the short-term elasticities divided by $(1-\gamma)$, where γ corresponds to the coefficient of the lagged dependent variable, *i.e.* $\frac{\beta_i}{(1-\gamma)}$. For instance, in Table 2 (column (1)), the estimated short-term *GDP per capita* elasticity is 0.4229 and its coefficient is significant at the 1% level. Dividing this elasticity by the estimate for $(1-\gamma = 1-0.6903)$ yields a value of 1.371, which would be the estimate for the long-term *GDP per capita* elasticity of the demand for mobility of the whole sample. Table 5 sums up the estimated short-term elasticities of both *GDP per capita* and *fuel price* and their corresponding computed long-term elasticities obtained in each of the three models.

<Insert Table 5 here>

According to our results (see Table 5), *GDP per capita* is found to be a significant determinant of mobility demand, stock of cars and new registrations in each model ('whole sample' and sample groups). *Fuel price* is statistically significant for only four of the 12 estimations, *i.e.* 30%. When statistically significant, the estimated *GDP per capita* and *fuel price* elasticities have the expected sign, *i.e.* positive for *GDP per capita* and negative for *fuel price*. The results are within the range of values found in the literature (Goodwin, 1992; Litman, 2013; Dunkerley et al., 2014). Elasticities with respect to *GDP per capita* is generally more than unity in the long run and 3 to 4 times higher than elasticities with respect to *fuel price*. We also observe profound differences in elasticities estimates between the three groups.

For mobility, short-term elasticities with respect to *GDP per capita* lie in the range 0.28 to 0.42 while long-term elasticities fall within a range of 1.09 to 1.37. These elasticies contain both direct (increase in demand for mobility) and indirect (increase in car ownership) effects (Dunkerley et al., 2014). *Fuel price* coefficients are statistically significant for the whole sample and the third group, meaning that fuel price policy measures may be effective to reduce road traffic in richer European countries. Short run elasticity with respect to *fuel price* falls within a range of -0.09 to -0.11. Long-term elasticities lie in the range -0.35 to -0.37. These elasticities would probably have been higher if they were estimated with respect to total vehicle costs rather than with respect to *fuel prices* (Litman, 2013).

The major determinant of car stock is *GDP per capita*. Car stock reacts positively to *GDP per* *capita* mainly through changes in car ownership levels. The estimated short-term elasticities with respect to *GDP per capita* lie in the range 0.147 to 0.172 while long-run elasticities fall within a range of 0.49 to 1.14. *Fuel price* coefficient is not statistically significant. The changes in *fuel prices* do not necessarily lead to important changes in the vehicle fleet growth. Nevertheless, it may influence the composition of the car fleet, *i.e.* an increase in *fuel prices* may boost sales in the small and more fuel efficient car segment at the expense of the medium and large car segments (Leard et al., 2016).

Short-term *GDP per capita* elasticities of new cars demand lie in the range 0.55 to 1.22. Long-run *GDP per capita* elasticities falls within a range of 1.17 to 2.55. Many studies (McCarthy, 1996; Beck, 2003; Craft & Schmidt, 2005) previously estimated the income elasticities to be around 2 (Derimoglu & Yunculer, 2016). Our results indicate that *fuel price* elasticities of new cars sales in the European countries ('whole sample') are about -0.295 (short run) and -0.475 (long run). We also find statistically significant *fuel price* coefficient for the group 2. It corresponds to a short run elasticity of -0.22 and a long run elasticity of -1.02.

In our view, the most important highlight of this article rely on the sharp influence of the economic activity (as measured by *GDP per capita*) on the evolution of the road transport demand. According to our *GDP per capita* elasticities estimates, *GDP* growth will induce higher mobility and higher stock growth of cars in all European countries. If nothing is done to disconnect the evolution of these two aggregates, CO_2 emissions of the EU road transport sector should continue to increase over the next decade.

In terms of public policy insights, these results suggest that, given the low (or not significant) *fuel price* elasticities, a carbon tax or an increase of fuel prices may not be sufficient to counter the foreseeable increase of overall car use suggested by high *GDP per capita* elasticities. Highest gasoline prices or high carbon tax may incite motorists to use more efficient vehicles but it would probably be not enough to curve $\mathrm{CO_2}$ emissions. Thus, a combination of instruments (regulatory and economic) appears to be essential in order to reduce the energy consumption and CO_2 emissions of European transport sector. Our dynamic panel data modeling leads us to conclude that the magnitude of the influence of these policies may differ from one group of countries to the next. Countries will respond differently to the same policy as elasticities differ across clusters of countries. Taken together, these results encourage policymakers to design national-level measures lowering the purchase costs (such as scrappage scheme or subsidies for low carbon technologies) rather than specific action on fuel taxes in order to reduce $\mathrm{CO_2}$ emissions of the European transport sector.

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Variables	**Unit**	**Source**
Population		
Total population	number of inhabitants	World Bank
Urban population	%	World Bank
Population density	inhabitants/km^2	World Bank
Unemployment rate	%	World Bank
Share of population $>$ 65 yrs old	%	World Bank
Road Network		
Total Road network	km	UNECE
Motorways	%	UNECE
Road density	km/km^2	UNECE
Economics		
GDP	Euros at constant price and exchange rate (2005)	Global energy
GDP per capita	Euros at constant price and exchange rate (2005) per capita	Global energy
Mobility and automotive market		
Total mileage by cars	km	Odysee
Mileage by cars	km per car	Odysee
Stock of cars	number of cars	Odysee
Registration of new cars	number of cars	Odysee
Car ownership	number of cars per 1000 inhabitants	Odysee
Fuels and fuel market		
Average consumption of cars	liters per 100km	Odysee
Gasoline price	Price in national currency of unleaded gasoline (taxes included)	Global energy
Diesel price	Price in national currency of diesel (taxes included)	Global energy
The 29 European countries and their clustering into three more homogenous groups		
Group 1	Bulgaria, Croatia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania	Authors *
Group 2	Cyprus, Czech Republic, Greece, Malta, Portugal, Slovak Republic, Slovenia, Spain	Authors *
Group 3	Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Norway, Sweden, the United Kingdom	Authors *
Groups	Dummy variable which take the values 1, 2 or 3 if the country under consideration belongs respectively to the group 1, 2 or 3	Authors *

NB: Data are given on a yearly and national basis, unless otherwise.

* Countries have been grouped *via* a principal component analysis.

Table 1: Variables in the database

	Mobility (Whole sample)	Mobility (Group 1)	Mobility (Group 2)	Mobility (Group 3)
$Mobility_{i,t-1}$	.6903***	.6424***	.7527***	.7432***
	(.1061)	(.1604)	(.0896)	(.1091)
GDP per capita	.4249***	.4076**	.2808**	.2805***
	(.1026)	(.1954)	(.1144)	(.061)
Fuel price	-.1145***			.09158***
	(.0217)			(.025)
Average consumption	-.3912***		-.2886*	-.1883**
	(.1177)		(.1548)	(.0767)
Constant	-	2.802**	2.467**	2.459**
		(1.224)	(.9967)	(1.127)
Groups	1.27***	-	-	-
	(.4573)			
Number of groups	21	6	6	11
Number of observations	419	108	127	229
Number of instruments	65	43	64	65
Wald chi2 (*P-value*)	2621.94 (0.00000)	644.23 (0.00000)	1584.26 (0.00000)	1770.13 (0.00000)
m1 (*P-value*)	-2.5377 (0.0112)	-2.0212 (0.0433)	-2.1498 (0.0316)	-2.1265 (0.0335)
m2 (*P-value*)	-.01429 (0.9886)	.5745 (0.5656)	-1.271 (0.2037)	.14959 (0.8811)

Table 2: The determinants of mobility demand

	Stock of cars (Whole sample)	Stock of cars (Group 1)	Stock of cars (Group 2)	Stock of cars (Group 3)
$Stock\ of\ cars_{i,t-1}$	.8019***	.6741***	.8591***	.8361***
	(.0238)	(.1401)	(.034)	(.0181)
GDP per capita	.1719***	.1598***	.1612***	.1477***
	(.0164)	(.0462)	(.0264)	(.0181)
Average consumption		-.7098***		
		(.2138)		
Constant	-	1.421***	-.2824***	-.1877***
		(.2806)	(.0734)	(.0762)
Groups	-.0975***	-	-	-
	(.0205)			
Number of groups	29	4	8	12
Number of observations	703	75	181	360
Number of instruments	63	44	63	63
Wald chi2 (*P-value*)	2618.77 (0.00000)	0.2342 (0.00000)	6767.06 (0.00000)	10925.91 (0.00000)
m1 (*P-value*)	-2.3895 (0.0169)	-.80844 (0.4188)	-1.4264 (0.1537)	-1.7542 (0.0794)
m2 (*P-value*)	-.29404 (0.7687)	1.1896 (0.2342)	.31463 (0.7530)	.99217 (0.3211)

Table 3: The determinants of vehicle inventory

	New registrations (Whole sample)	New registrations (Group 1)	New registrations (Group 2)	New registrations (Group 3)
New registrations$_{i,t-1}$	.3786***	.4682***	.7829***	.431***
	(.0993)	(.0494)	(.138)	(.0699)
GDP per capita	1.222***	.6882***	.5556**	.6705***
	(.25)	(.116)	(.253)	(.126)
Fuel price	-.295***		-.2223***	-
	(.119)		(.0675)	
Constant	-	-2.625***	-1.838***	-2.679***
		(.449)	(.742)	(.371)
Groups	-1.808***	-	-	-
	(.345)			
Number of groups	29	8	8	12
Number of observations	668	129	171	356
Number of instruments	64	40	64	63
Wald chi2 (*P-value*)	139.95 (0.00)	169.73 (0.00)	38.49 (0.00)	212.31 (0.00)
m1 (*P-value*)	-2.3922 (0.0167)	-2.1921 (0.0284)	-2.0863 (0.0370)	-2.736 (0.0062)
m2 (*P-value*)	-.54156 (0.5881)	1.5342 (0.1250)	.42289 (0.6724)	-2.2816 (0.2873)

Table 4: The determinants of new registrations

			(Whole sample)	(Group 1)	(Group 2)	(Group 3)
GDP per capita						
	Mobility					
		short-term	.4249	.4076	.2808	.2805
		long-term	1.371	1.140	1.135	1.092
	Stock of cars					
		short-term	.1719	.1598	.1612	.1477
		long-term	0.868	0.49	1.144	0.901
	New registrations					
		short-term	1.222	.6882	.5556	.6705
		long-term	1.967	1.294	2.559	1.178
Fuel price						
	Mobility					
		short-term	-.1145	-	-	-0.09158
		long-term	-.370	-	-	-0.357
	Stock of cars					
		short-term	-	-	-	-
		long-term	-	-	-	-
	New registrations					
		short-term	-.295	-	-.2223	-
		long-term	-0.475	-	-1.024	-

Table 5: Short-run and long-run elasticities